License Plate Location Based on Multi Agent Systems

M. Ebrahimi
Department of Falavarjan Azad university,Iran
hoo_Ebrahimi@yahoo.com

R. Monsefi
faculty of engineering Ferdowsi university, Mashad Iran
rmonsefi@ferdowsi.um.ac.ir

S. Ildarabadi
Department of Computer Engineering Azad university,Iran
sedigheh_ildarabadi@yahoo.com

M. R. Akbarzadeh
faculty of engineering Ferdowsi university, Mashad Iran
akbarzadeh@ieee.org

M. Habini
faculty of Falavarjan Azad university,Iran

Abstract

In this paper, a new algorithm for vehicle license plate location is proposed, on the basis of multi agent systems. The algorithm was tested with 400 natural-scene gray-level vehicle images of different backgrounds and ambient illumination. The camera focused in the plate, while the angle of view and the distance from the vehicle varied according to the experimental setup. The license plates properly segmented about 99 percent of input images (99%).

Keywords: Image processing, machine vision, multi agent system, license plate location (LPL)

1. Introduction

During the past few years, intelligent transportation systems (ITSs) have had a wide impact in people's life as their scope is to improve transportation safety and mobility and to enhance productivity through the use of advanced technologies.[1] In this paper, we combined computer vision methods by use of multi agent systems contents for license plate location (LPL).

2. Overview

LPL algorithms reported in previous research are barrelful. All papers are covered according to their major contribution in this section. The major goal of this section is to provide a brief reference source for the researchers involved in license plate identification and recognition, regardless of particular application areas (i.e., billing, traffic surveillance etc.).

As far as extraction of the plate region is concerned, techniques based upon combinations of edge statistics and mathematical morphology [2]–[5] featured very good results. In these methods, gradient magnitude and their local variance in an image are computed. They are based on the property that the brightness change in the license plate region is more remarkable and more frequent than otherwise. Block-based processing is also supported [6]. Then, regions with a high edge magnitude and high edge variance are identified as possible license plate regions. Since this method does not depend on the edge of license plate boundary, it can be applied to an image with unclear license plate boundary and can be implemented simply and fast. A disadvantage is that edge-based methods alone can hardly be applied to complex images, since they are too sensitive to unwanted edges, which may also show high edge magnitude or variance (e.g., the radiator region in the front view of the vehicle). In spite of this, when combined with morphological steps that eliminate unwanted edges in the processed images.

Color or gray-scale-based processing methods are proposed in the literature for license plate location [7]–[11]. Crucial to the success of the color (or gray level)-based method is the color (gray level) segmentation stage. On the other hand, solutions currently available do not provide a high degree of accuracy in a natural scene as color is not stable when the lighting conditions change. Since these methods are generally color based, they fail at detecting various license plates with varying colors. Though color processing shows better performance, it still has difficulties recognizing a car image if the image has

1-4244-1148-3/07/$25.00 ©2007 IEEE.

many similar parts of color values to a plate region. An enhanced color texture based method for detecting license plates (LPs) in images was presented in [12]. The system analyzes the color and textural properties of LPs in images using a support vector machine (SVM) and locates their bounding boxes by applying a continuous adaptive mean shift (CAMShift) algorithm. The combination of CAMShift and SVMs produced efficient LP detection as time-consuming color texture analysis for less relevant pixels were restricted, leaving only a small part of the input image to be analyzed. Yet, the proposed method still encountered problems when the image was extremely blurred or quite complex in color.

An example of time-consuming texture analysis is presented in [13], where a combination of a "kd-tree" data structure and an "approximate nearest neighbor" was adopted. The computational resource demand of this segmentation technique was the main drawback, since it yielded an execution time unacceptable for LPR (34 s).

In [14], a method is developed to scan a vehicle image with N row distance and count the existent edges. If the number of the edges is greater than a threshold value, this manifests the presence of a plate. If in the first scanning process the plate is not found, then the algorithm is repeated, reducing the threshold for counting edges. The method features very fast execution times as it scans some rows of the image. Nonetheless, this method is extremely simple to locate license plates in several scenarios, and moreover, it is not size or distance independent.

Fuzzy logic has been applied to the problem of locating license plates [15]–[17]. The authors made some intuitive rules to describe the license plate and gave some membership functions for the fuzzy sets "bright," "dark," "bright and dark sequence," "texture," and "yellowness" to get the horizontal and vertical plate positions, but these methods are sensitive to the license plate color and brightness and need longer processing time from the conventional color-based methods. Consequently, in spite of achieving better results, they still carry the disadvantages of the color-based schemes.

Gabor filters have been one of the major tools for texture analysis. This technique has the advantage of analyzing texture in an unlimited number of directions and scales. A method for license plate location based on the Gabor transform is presented in [18]. The results were encouraging (98% for LP detection) when applied to digital images acquired strictly in a fixed and specific angle, but the method is computationally expensive and slow for images with large analysis. For a two-dimensional (2-D) input image of size $N \times N$ and a 2-D Gabor filter of size $W \times W$, the computational complexity of 2-D Gabor filtering is in the order of W^2N^2, given that the image orientation is fixed at a specific angle. Therefore, this method was tested on small sample images and it was reported that further work remain to be done in order to alleviate the limitations of 2-D Gabor filtering.

Genetic programming (GP) [19] and genetic algorithms (GAs) [20], [21] were also implemented for the task of license plate location. GP is usually much more computationally intensive than the GAs, although the two evolutionary paradigms share the same basic algorithm. The higher requirements in terms of computing resources with respect to the GAs are essentially due to the much wider search space and to the higher complexity of the decoding process as well as of the crossover and mutation operators. The authors indicate that the research carried out in [19]–[21], despite being encouraging, is still very preliminary and requires a deeper analysis. While the authors in [19] and [21] did not report clearly the results of their work, in [20], the identification ratio reached 80.6% on average, with a very fast execution time (0.18 s). In [21], the GA was presented for license plate location in a video sequence. In the method using Hough transform (HT), edges in the input image are detected first. Then, HT is applied to detect the license plate regions. In [22], the authors acknowledge that the execution time of the HT requires too much computation when applied to a binary image with great number of pixels. As a result, the algorithm they used was a combination of the HT and a Contour algorithm, which produced higher accuracy and faster speed so that it can be applied to real-time systems. However, as HT is very sensitive to deformation of boundaries this approach has difficulty in extracting license plate region when the boundary of the license plate is not clear or distorted or the images contain lots of vertical and horizontal edges around the radiator grilles. This method achieved very good results when applied to close shots of the vehicle.

In [23], a strong classifier was trained for license plate identification using the adaptive boosting (AdaBoost) algorithm. When executed over several rounds, AdaBoost selects the best performing weak classifier from a set of weak classifiers, each acting on a single feature, and, once trained, combines their respective votes in a weighted manner. This strong classifier is then applied to sub regions of an image being scanned for likely license plate locations. Despite the fact that this paper has shown to be promising for the task of license plate detection, more work needs to be done. Additionally, since the classifier is applied to sub regions of specific dimension, the system could not detect plates of different size or images acquired from different view/distance without retraining.

A wavelet transform-based method is used in [24] for the extraction of important contrast features used as guides to search for desired license plates. The major advantage of wavelet transform, when applied for license plate location, is the fact that it can locate multiple plates with different orientations in one image. Nevertheless, the method is unreliable when the distance between the vehicle and the acquisition camera is either too far or too close.

Symmetry is also used as a feature for car license plate extraction. The generalized symmetry transform (GST) produces continuous features of symmetry between two points by combining locality constraint and reflectional symmetry. This process is usually time consuming because the number of possible symmetrical pixels in the image is huge. Moreover, a rotated or perspectively distorted car license plate image is impossible to detect. In [25], the

authors propose a scan line decomposition method of calculating GST in order to achieve considerable reduction of computational load. The result is indeed encouraging as far as the computational time is concerned, but since the scan line-based GST evaluates symmetry between a pair of edge pixels along the scan lines, the execution time increases linearly with respect to the radius of the searching area. Thus, the algorithm set limits to its effective distance, as a closer view of the plate results to increased processing time. Moreover, this approach is insufficient when rotated or distorted plates appear.

In addition, various neural-network architectures [26]–[28] are proposed and implemented for plate identification, namely the pulse coupled neural networks (PCNNs), the time delay neural networks (TDNNs), and the discrete time cellular neural networks (DTCNNs). In [27], it was demonstrated that the computationally most intensive steps in LPR could be realized by DTCNNs. The tests demonstrated that the DTCNNs were capable of correctly identifying 85% of all license plates. The total system contained several DTCNNs whose templates were constructed by combining the appropriate morphological operations and traditional filter techniques. This paper was an extension of a previous work of the authors [16], where they used fuzzy logic rules for license plate location. In [27], the PCNN is used to generate candidate regions that may contain a license car plate. Candidate regions are generated from pulsed images, output from the PCNN. The results of these applications indicate that the PCNN is a good preprocessing element. The results have shown than in spite of being encouraging (85% for plate detection), a lot of research still remains to be performed. Impressively good results were achieved in [28], where the TDNN schema was implemented. TDNN is a multilayer feedforward network whose hidden neurons and output neurons are replicated across a time. It has the ability to represent relationships between events in time and to use them in trading relations for making optimal decisions. In this paper, the license plate segmentation module extracts the license plate using two TDNNs as filters for analyzing color and texture properties of the license plate. The results were remarkable in terms of speed and accuracy with the drawback of computational complexity, but as the method is color based, it is also country specific. It should be also noted that as the system was designed to check a fixed region, there was a rough knowledge of possible plate location, which also explains the fast execution time versus the complexity of the algorithm.

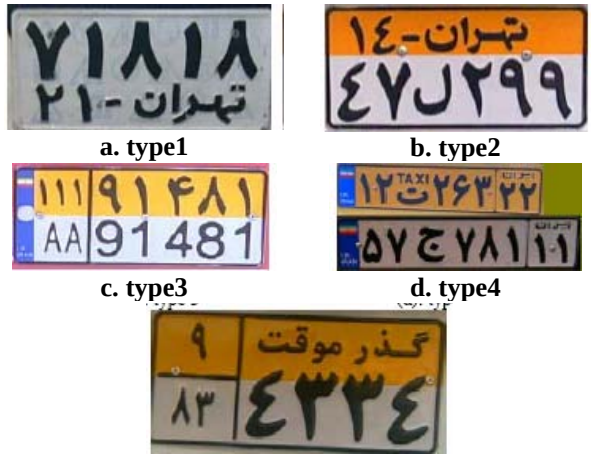
In [29], a method based on vector quantization (VQ) to process vehicle images is presented. This technique makes it possible to perform superior picture compression for archival purposes and to support effective location at the same time. Compared to classical approaches, VQ encoding can give some hints about the contents of image regions. Such additional information can be exploited to boost location performance.

A sensing system with a wide dynamic range has been manufactured in [30] to acquire fine images of vehicles under varied illumination conditions. The developed sensing system can expand the dynamic range of the image (almost double in comparison with conventional CCDs) by combining a pair of images taken under different exposure conditions. This was achieved as a prism beam splitter installed a multilayered filter, and two charge-coupled devices are utilized to capture those images simultaneously. [1]

In this paper, a new algorithm for vehicle license plate location is proposed, on the basis of multi agent systems. The algorithm was tested with 1334 natural-scene gray-level vehicle images of different backgrounds and ambient illumination. The camera focused in the plate, while the angle of view and the distance from the vehicle varied according to the experimental setup. The license plates properly segmented were 1287 over 1334 input images (96.5%).

3. License plates types

There are five different types of Iranian vehicles, which samples of these five types are display in fig.1.



a. type1 **b. type2**

c. type3 **d. type4**

e. type5

Figure 1. The different Persian License Plates

4. LPL based on tow Agent System

We divide all LPL methods to fast and rhadamanthine methods. Actual systems usually use morphological techniques for finding location of license plates. But for increasing to speed, the methods such as *"finding some edges (i.e. vertical edges) and counting them with threshold [14]"* is used. A disadvantage of this *"high speed methods" (i.e. [14])* is that, they alone can hardly be applied to complex images, since they are too sensitive to unwanted edges, which may also show high edge magnitude or variance (e.g., the radiator region in the front view of the vehicle). In these methods accuracy reduce for images with extremely complex.

We individualize images with extremely complex, and use methods with more accurate, for them. In applications

such as *"highway tolling"* that car speed is high, and numbers of vehicles are very much, the speed of LPL system must be very high.

Problem complexity is explicit here; Because of we must increase processes, without time consuming. We use multi agent system for beat this problem. In our system, we use two agents, speed agent and accuracy agent. Speed agent use express methods; In this paper we use multiple interlacing [14] for this agent. Accuracy agent use accurate methods to find license plate in complex images. We use gabor transform for this agent. Gabor transform get our arbitrary directions of edges accurately. Fig. 2 is our LPL overview, The whole input images have been gave to speed agent; Then complexity of input images are calculated; If it is more than threshold must to be get to accuracy agent.

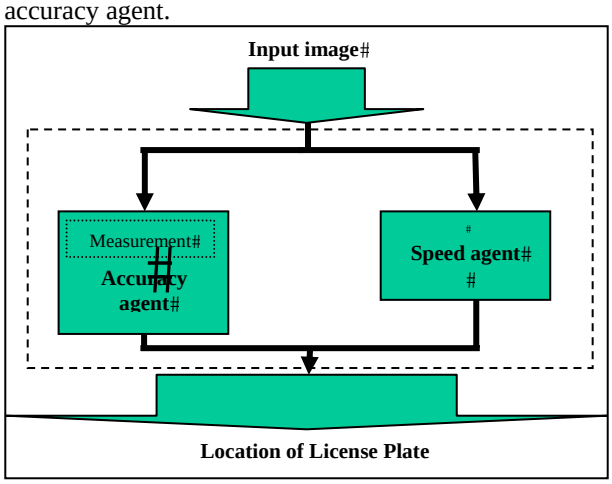


Figure 2. LPL based on SpeedAgent & Acuracy System

3. Experimental Analysis and Results

Experiments have been performed to test the Persian LPL system. The system is designed in windows with Matlab for location of Persian license plates.

The experimental images are from [14], that they were board with gray scale of size 640x480. The test images were taken under various illumination, size and types of license plate conditions. The experiments for the Persian LPL system were performed under different illumination, different distance and various types of license plate. Table 1 gives results for the Persian LPL system that displayed in fig.1.

Table 1. Evaluation performance with different methods for Persian license plate

methods	Number of license plats	Percentage location
[14]	400	95%
This method	400	99%

4. Conclusion

We presented, in this paper, a new algorithm for vehicle license plate location on the basis of multi agent systems for Iranian license plates.

The algorithm was tested in natural-scene gray-level vehicle images of different backgrounds and ambient illumination. The camera focused in the plate, while the angle of view and the distance from the vehicle varied according to the experimental setup. The performance increased.

5. References

[1] Christos Nikolaos E. Ioannis E. Vassili Loumos, Eleftherios Kayafas, "A License Plate-Recognition Algorithm for Intelligent Transportation System Applications" IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, VOL. 7, NO. 3, SEPTEMBER 2006

[2] F. Martín, M. García, and L. Alba, "New methods for automatic reading of VLP's (Vehicle License Plates)," in Proc. IASTED Int. Conf. SPPRA, Jun. 2002. [Online]. http://www.gpi.tsc.uvigo.es/pub/papers/sppra02.pdf

[3] B. Hongliang and L. Changping, "A hybrid license plate extraction method based on edge statistics and morphology," in Proc. ICPR, 2004, pp. 831–834.

[4] D. Zheng, Y. Zhao, and J. Wang, "An efficient method of license plate location," Pattern Recognit. Lett., vol. 26, no. 15, pp. 2431–2438, Nov. 2005.

[5] S. Z. Wang and H. M. Lee, "Detection and recognition of license plate characters with different appearences," in Proc. Conf. Intell. Transp. Syst., 2003, vol. 2, pp. 979–984.

[6] H.-J. Lee, S.-Y. Chen, and S.-Z. Wang, "Extraction and recognition of license plates of motorcycles and vehicles on highways," in Proc ICPR, 2004, pp. 356–359.

[7] T.-H. Wang, F.-C. Ni, K.-T. Li, and Y.-P. Chen, "Robust license plate recognition based on dynamic projection warping," in Proc. IEEE Int Conf. Netw., Sensing and Control, 2004, pp. 784–788.

[8] X. Shi,W. Zhao, and Y. Shen, "Automatic license plate recognition system based on color image processing," in Lecture Notes on Computer Science, vol. 3483, O. Gervasi et al., Eds. New York: Springer-Verlag, 2005, pp. 1159–1168.

[9] D. Yan, M. Hongqing, L. Jilin, and L. Langang, "A high performance license plate recognition system based on the web technique," in Proc. Conf. Intell. Transp. Syst., 2001, pp. 325–329.

[10] P. Comelli, P. Ferragina, M. N. Granieri, and F. Stabile, "Optical recognition of motor vehicle license plates," IEEE Trans. Veh. Technol., vol. 44, no. 4, pp. 790–799, Nov. 1995.

[11] S. Draghici, "A neural network based artificial vision system for license plate recognition," Int. J. Neural Syst., vol. 8, no. 1, pp. 113–126, Feb. 1997.

[12] K. I. Kim, K. Jung, and J. H. Kim, "Color texture-based object detection: An application to license plate localization," in Lecture Notes on Computer Science, vol. 2388, S.-W. Lee and A. Verri, Eds. New York: Springer-Verlag, pp. 293–309.

[13] J. Cano and J. C. Perez-Cortes, "Vehicle license plate segmentation in natural images," in Lecture Notes on Computer Science, vol. 2652, F. J. Perales et al., Eds. New York: Springer-Verlag, 2003, pp. 142–149.

[14] A. Broumandnia and M. Fathy, "Application of pattern recognition for Farsi license plate recognition," presented at the ICGST Int. Conf. Graphics, Vision and Image Processing (GVIP), Dec. 2005. [Online]. http://www.icgst.com/gvip/v2/P1150439001.pdf

[15] N. Zimic, J. Ficzko, M. Mraz, and J. Virant, "The fuzzy logic approach to the car numlber plate locating problem," in Proc. IIS, 1997, pp. 227–230.

[16] J. A. G. Nijhuis, M. H. ter Brugge, K. A. Helmholt, J. P. W. Pluim, L. Spaanenburg, R. S. Venema, and M. A. Westenberg, "Car license plate recognition with neural networks and fuzzy logic," in Proc. IEEE Int. Conf. Neural Netw., 1995, vol. 5, pp. 2232–2236.

[17] S.-L. Chang, L.-S. Chen, Y.-C. Chung, and S.-W. Chen, "Automatic license plate recognition," IEEE Trans. Intell. Transp. Syst., vol. 5, no. 1, pp. 42–53, Mar. 2004.

[18] F. Kahraman, B. Kurt, and M. Gökmen, "License plate character segmentation based on the gabor transform and vector quantization," in Lecture Notes on Computer Science, vol. 2869, A. Yazici and C. Sener, Eds. New York: Springer-Verlag, 2003, pp. 381–388.

[19] G. Adorni, S. Cagnoni, M. Gori, and M. Mordonini, "Access contro system with neuro-fuzzy supervision," in Proc. Conf. Intell. Transp. Syst., 2001, pp. 472–477.

[20] S. Yoshimori, Y. Mitsukura, M. Fukumi, and N. Akamatsu, "License plate detection using hereditary threshold determine method," in Lecture Notes in Artificial Intelligence, vol. 2773, V. Palade, R. J. Howlett, and L. C. Jain, Eds. New York: Springer-Verlag, 2003, pp. 585–593.

[21] Y. Cui and Q. Huang, "Extracting characters of license plates from video sequences," Mach. Vis. Appl., vol. 10, no. 5/6, pp. 308–320, Apr. 1998.

[22] T. D. Duan, T. L. Hong Du, T. V. Phuoc, and N. V. Hoang, "Building an automatic vehicle license plate recognition system," in Proc. Int. Conf. Comput. Sci. RIVF, 2005, pp. 59–63.

[23] L. Dlagnekovin License Plate Detection Using AdaBoost. La Jolla: Comput. Sci. Eng. Dept., Univ. California San Diego, Mar. 2004.[Online]. http://www.cse.ucsd.edu/classes/fa04/cse252c/projects/louka.pdf

[24] C.-T. Hsieh, Y.-S. Juan, and K.-M. Hung, "Multiple license plate detection for complex background," in Proc. Int. Conf. AINA, 2005, vol. 2, pp. 389–392.

[25] D.-S. Kim and S.-I. Chien, "Automatic car license plate extraction using modified generalized symmetry transform and image warping," in Proc. ISIE, 2001, pp. 2022–2027.

[26] M. H. ter Brugge, J. H. Stevens, J. A. G. Nijhuis, and L. Spaanenburg, "License plate recognition using DTCNNs," in Proc. IEEE Int. Workshop Cellular Neural Netw. and Appl., 1998, pp. 212–217.

[27] M. I. Chacon and A. Zimmerman, "License plate location based on a dynamic PCNN scheme," in Proc. Int. Joint Conf. Neural Netw., 2003, vol. 2, pp. 1195–1200.

[28] K. K. Kim, K. I. Kim, J. B. Kim, and H. J. Kim, "Learning-based approach, for license plate recognition," in Proc. IEEE Signal Process. Soc. Workshop, Neural Netw. Signal Process., 2000, vol. 2, pp. 614–623.

[29] R. Zunino and S. Rovetta, "Vector quantization for license plate location and image coding," IEEE Trans. Industrial Electron., vol. 47, no. 1, pp. 159–167, Feb. 2000.

[30] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, "Robust license plate recognition method for passing vehicles under outside environment," IEEE Trans. Veh. Technol., vol. 49, no. 6, pp. 2309– 2319, Nov. 2000.